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Image Fusion using HVS in Discrete Wavelet Transform domain

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Abstract

The aim of image fusion is to generate high-quality images using the information collected from the source images. The fused image contains more information than any of its source images. Image fusion using transform method is more efficient than spatial method. The characteristics of the Human visual system (HVS) are explored in the discrete wavelet transform (DWT) domain. In this paper, we have used HVS weightage matrix in the transform domain to select appropriate information from multiple images to obtain a fused image. Two steps are involved to obtain high quality fused image. The first step involves the application of the DWT to the source images. The second step is to identify the important sub bands using the HVS weights. Hence, the perceptual important information is selected from different source images to form the fused image. Finally, qualitative and quantitative information is considered for image fusion. This technique is more useful for the images processed by using JPEG2000 technique. It is time saving and simpler when the fused image desires to be saved or transmitted in JPEG2000 format. The proposed algorithm is assessed by mutual information (MI), edge strength and orientation preservation (ESOP), feature similarity (FSIM) index, and normalized cross correlation (NCC). The experimental results establish the superiority of our proposed method over other state-of-the-art techniques for image fusion.

Keywords: Human Visual System, Contrast Sensitivity Function, Discrete Wavelet Transform, Image Fusion.

Nomenclature:

HVS	Human Visual System
DWT	Discrete Wavelet Transform
CSF	Contrast Sensitivity Function
MI	Mutual Information
FSIM	Feature Similarity
NCC	Normalized Cross Correlation

1. Introduction

Since the past few decades, image processing approaches are being used to improve the visual quality of the images. Digital image fusion is one of the novel image processing approaches. Image fusion is a technique that acquires the related information from various source images to form a fused image. The resultant fused image contains more information than any of the source images. The image fusion technique can be implemented in two domains, spatial domain and transform domain. The spatial domain method is based on mean, standard deviation, variance, gradient, spatial frequency, and other spatial features. On the other hand, transform domain is of two types. One is block-based transform, and the other one is multi-resolution transform. Some of the block-based transform techniques are Discrete Cosine Transform (DCT), Discrete Sine Transform (DST), Walsh, Hadamard, Haar, and Slant transform. Image processing using block based methods suffer with blocking artifacts. Some of the multi-resolution transforms are continuous wavelet transform (CWT), discrete wavelet transforms (DWT), dual tree discrete wavelet transform (DTDWT), Curvelet transforms (CrT), Contourlet transforms (CT), Non Sub Sampled Contourlet transforms (NSCT), Shearlet transforms.
Transforms in combination with statistical measures help to identify vital information in the source images. Multi scale decomposition based fusion techniques are

popular [1]. These techniques involve grouping of the source images based on a parameter called the activity level measure. The summation can be finalized by selecting the band coefficients of the source images with higher activity levels. The fused image is finally obtained by performing inverse multi scale transform operations. DWT is a multi resolution transform method used for image fusion [2].

Most of the spatial domain image fusion approaches are complex and time-consuming and hence, are not suitable to the real-time applications. In most of the communications, data and the images are compressed, prior to transmission, using the JPEG /JPEG2000 code-stream format. JPEG methods suffer with blocking artifacts. Hence, JPEG2000 procedure is considered in this work. JPEG2000 uses DWT. There are many advantages with the JPEG2000. Those are the resolution accuracy, choice of lossless or lossy compression, flexible file format, vast dynamic range support, full support of transparency and progressive transmission.

Human Visual System (HVS) mask is useful in identifying the perceptual important information. The best quality results are observed by adopting the HVS model for image processing. HVS is comprised of attributes like sensitivity, brightness adaptation level, and texture activity. Shutao et al. [3] proposed fusion algorithms based on multi resolution transforms. A comparative study was performed by Sivasubramani and Soman [4] on image fusion algorithms. In most of the literature, the HVS weights of DWT are determined to use the contrast sensitive function (CSF) mask for watermarking applications [5-12,23, 24]. The maximum level of local energy-based image fusion in DWT domain is explored by Humin Lu et al. [13]. Paolo Gamba [14] had conducted research on remote sensing data fusion. Multi sensor visual information was collected and reconstructed by Fredric et al. [15], to calculate the image depth. K. S. Thyagarajan [25] described about the image compression techniques using DWT. Also, JPEG2000 is a recommendation for lossy and lossless encoding and reconstruction of an image. The codestream syntax is specified which convert the source image data to output or compressed image data. Using the CSF, the HVS weights of each detail bands and an approximation band are calculated. The most significant information can be obtained with help of quantized HVS weights. Beegan [9] also proposed an efficient watermarking technique HVS weights. The same method of identification of significant information is used in the proposed method for fusion application.

In the DWT domain, the maximum absolute value of the corresponding band coefficients, with HVS weightages at each decomposition level, is selected as the activity level [1]. In previous studies, DWT was used in many applications, such as compression, watermarking, and Image fusion. DWT + maximum selection rule and DWT+ average based image fusion are popular [1- 3]. These methods are fail to identify visually important information of the source images. In this work, we proposed DWT + HVS to identify the perceptual important sub bands in the source images for image fusion.

The rest of the paper is organized as follows. Section 2 describes HVS weightage calculation in the DWT domain, and the proposed fusion algorithm is explained in detail in Section 3. We have discussed the results of our experiments to test the performance of our proposed method in Section 4 and offered our conclusions in Section 5.

2. HVS weightage calculation in the DWT domain

In the digital images, noise is present while capturing images with the digital camera, preprocessing, coding, and transmission. 2D-DWT is an efficient multi resolution transform method used for exploiting the 2D correlation of the image. The 2D-DWT for an N x N image size $f(x,y)$ is defined as

$$\Psi_{\varphi}(j_0,u,v)=\frac{1}{\sqrt{(N)(N)}}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y)\phi_{j_0,u,v}(x,y) \qquad (1)$$

$$\Psi_{\psi}^{i}(j,u,v)=\frac{1}{\sqrt{(N)(N)}}\sum_{x=0}^{N-1}\sum_{y=0}^{N-1}f(x,y)\psi^{i}_{j,u,v}(x,y) \qquad (2)$$

where $\varphi_{j_0,u,v}(x,y)=2^{j/2}\phi(2^{j}x-u,2^{j}y-v)$ is the 2D scaling function,

$\psi^{i}_{j,u,v}=2^{j/2}\psi^{i}(2^{j}x-u,2^{j}y-v)$ is the translated basis function,

$i=\{H,V,D\}$ is the superscript that assumes the values rows, columns, and diagonals, j is the scaling function, and $u=v=0,1,2,3...2^{j}-1$.

The $\Psi_{\phi}(j_0,u,v)$ coefficients define an approximation of $f(x,y)$ at scale j_0, and the $\Psi_{\psi}^{i}(j,u,v)$ coefficients add horizontal, vertical, and diagonal details for scales $j \geq j_0$.

Wavelet decomposition of an image is a two-dimensional filtering operation. An octave sub sampling is performed to obtain the l number of levels of decomposition [3]. Since the scaling functions and wavelet functions are separable, the image decomposition can be computed with a separable extension of the two one-dimensional decompositions along the rows and columns. At every stage of transform, the image is divided into four sub-images. As DWT has good localization in time and frequency domains, introducing its inherent scaling property to transform the whole image has better identification and higher flexibility. The input image can cause a lot of variations in the distribution of energy between

DWT coefficients due to lack of shift invariance. The major applications of DWT are in data compression, biomedical engineering, non-destructive evaluation, denoising, and source and channel encoding.

HVS is a mathematical model developed for human eye vision that regard the sensitivity of the eye to noise changes, local brightness, and local texture activities in the bands [16]. The weighing function to determine the HVS is calculated as the combination of three terms in equation (3):

$$S_l^i(u,v) = \left(\Theta(l,i).\Lambda(l,u,v).\mathrm{E}(l,u,v)^{0.2}\right)/2 \qquad (3)$$

where l represents the level of decomposition, $\Theta(l,i)$ represents the sensitivity of noise changes, $\Lambda(l,u,v)$ indicates the brightness, and $\mathrm{E}(l,u,v)$ indicates the texture activity. Using the equation (3), the HVS weights are calculated.

3. Proposed method

3.1. General block diagram

The general block diagram for proposed image fusion is given in Figure 1. In the experiment, a common framework of a JPEG 2000 encoder is used in the proposed image fusion method. Any number of source images can be considered. The fusion process is given I Figure 2.

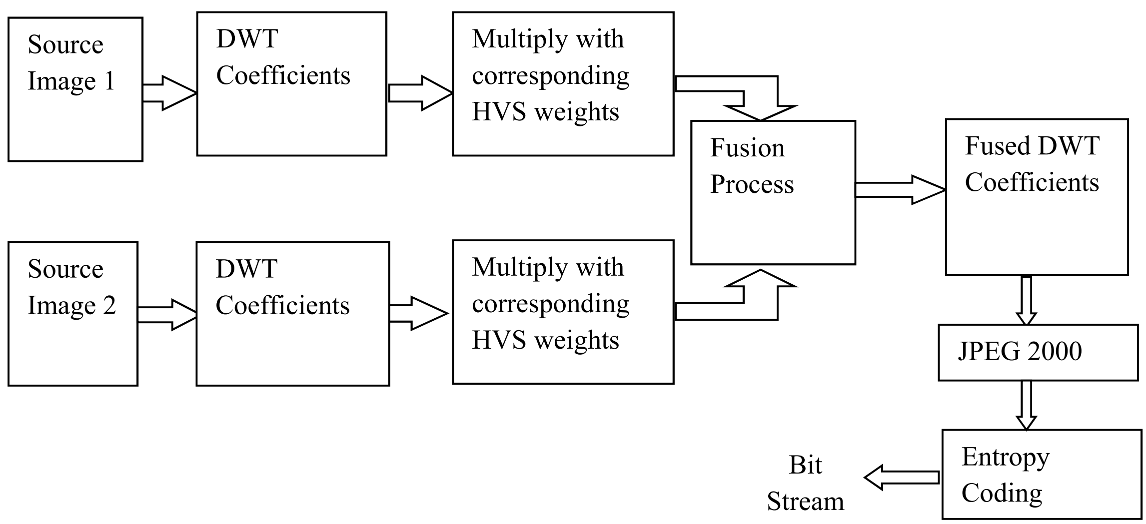

Figure1. The block diagram of the fusion process

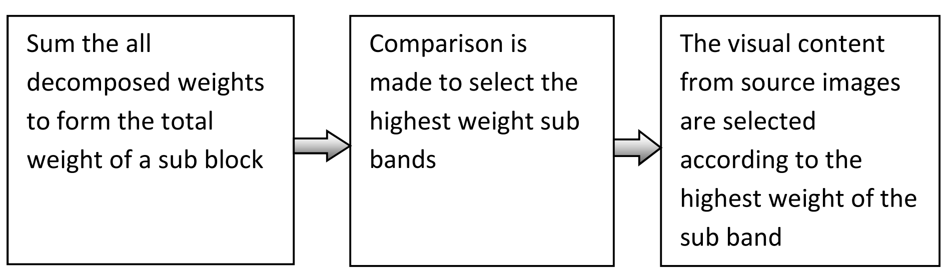

Figure2. The fusion process

The most of work has been dedicated to understand the human visual system (HVS) and applying this knowledge to image processing applications. In image fusion algorithms there has been a need of good metrics for image quality assessment of multiple images. In DWT domain, the HVS can be used to select perceptually important coefficients for fusion. HVS is comprised of attributes like sensitivity, brightness and texture activity. Hence, it is preferred. DWT is the backbone for JPEG2000 application. Hence, DWT is preferred. It is simple and time saving, when the fused image desires to be transmitted or saved in JPEG2000 format.

The general image fusion procedure, applying the 2D-DWT in each source image, is explained below. The HVS weightage of all sub bands of 2D-DWT are calculated. Response for each band is calculated using HVS weightage of the corresponding band. High-response bands are considered for image fusion.

$$\Psi(u,v) = [\Psi_{\varphi}(j_0,u,v) + \Psi_{\psi}^{i}(j,u,v)] * S_{l}^{i}(u,v) \quad (4)$$

The total weight of each sub band is calculated by summing up all the weighted signals.

$$w_t = \sum\sum \Psi(u,v) \quad (5)$$

The absolute value of the activity level is given in equation (6)

$$Wt = |w_t| \quad (6)$$

The second step in fusion is selecting the right sub band by using activity level:

$$A_F(u,v) = \begin{cases} A_1(u,v) & W_{t1} > W_{t2} \\ A_2(u,v) & otherwis \end{cases} \quad (7)$$

where $A_1(u,v)$ is the resultant of the first image sub band and $A_2(u,v)$ is the resultant of the second image sub band. The comparison is performed between the sub bands, and the high-response sub band is selected. Likewise, all the sub band coefficients are selected to get a fused image.

3.2. Algorithm for proposed approach

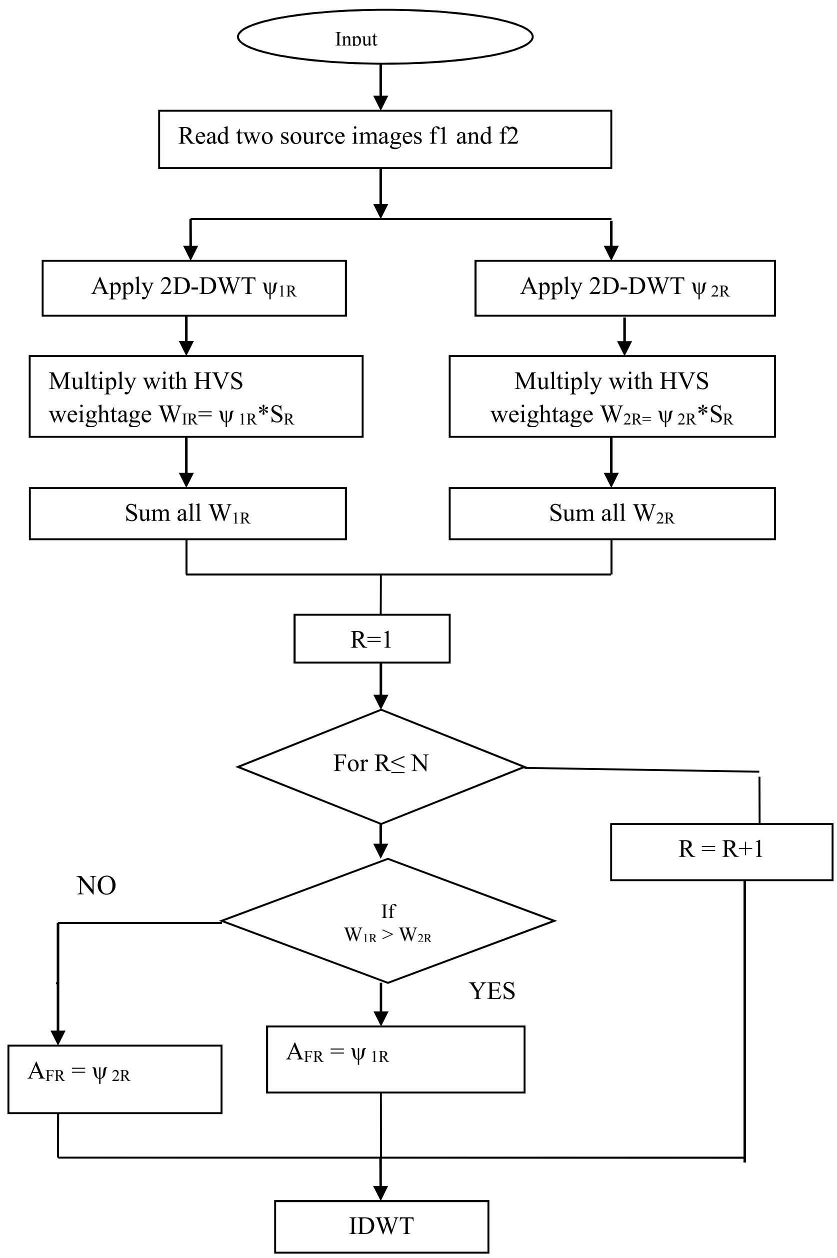

Figure 3. Flow chart for proposed method

The steps involved in the proposed fusion algorithm are given below:

- Considering two or more source images for collecting information for fusion.
- Applying the DWT on each source image as given in equation (2).
- Calculating corresponding HVS weightage using equation (3).
- Multiplying each sub band coefficient with the corresponding HVS weights as per equation (4).
- The response of each sub band coefficient is calculated using equations (5) and (6).
- The weights of sub band s are compared, and the high-response sub band is selected from the source images by using equation (7).
- Inverse DWT is applied for high-response sub bands to get the fused image.

4. Experimental results and discussion

In this section, the experimental results are described for the proposed approach in comparison to the state-of-the-art image fusion techniques. In Figure 4, the source images are given. The proposed method is clearly described in the flow chart given in Figure 3.

Figure3. Source images

4.1. Fusion metrics for performance evaluation

The criteria for image evaluation are based on the features like the amount of information transferred and the edges compared in view of the input and output images. In general, the fusion metrics, based on the input sources and the fused image, are useful in obtaining the visual quality that is optimal to the benchmark. Mutual Information (MI), one of the fusion metrics derived by Cvejic et al. [16], is used to determine the amount of information contained in the fused image from the source images. MI can be proposed for non-reference image fusion algorithms [16, 17]. The measuring unit for MI is a bit. Feature similarity (FSIM) index is a metric designed particularly for the image quality assessment (IQA) of an image that refers the fusion based on HVS [18]. FSIM is calculated basically in two steps, one is Phase Congruent (PC) that is a contrast invariant dimensionless measure and the second is Gradient Magnitude (GM) that is employed as an another feature assessment without affecting the perception of HVS and the quality of the fused image. NCC is a metric used to achieve normalized random information correlated between the benchmarks of input source images and the fused output image [16]. Xydeas and Petrovic [20] proposed an assessment of the fusion performance with the edge information which is transferred from the source images to the fused images, which is calculated by using a fusion metric the edge strength and orientation preservation (ESOP) ($Q^{f_1 f_2 / f_S}$). A Sobel filter that is an edge operator is applied to calculate the ESOP [21]. The elapsed time was calculated with the help of 1.0 Windows Experience Index, Intel(R) Core (TM) I5-3470 CPU, RAM- 4.00GB, and 64-bit Operating System. MATLAB R2007.7b version was used.

Table 1: Experimental results for various images using ‘Haar’ filter

Fusion rule	Multi-focus image	Filter	MI	ESOP	FSIM	NCC	Elapsed time in sec
DWT+HVS (proposed)	Lena	Haar	**3.7678**	**0.8583**	**0.9994**	**0.9933**	**0.161452**
DWT (max. selection) [3]	Lena	Haar	1.7972	0.5147	0.9905	0.9511	0.175921
DWT (Average) [4]	Lena	Haar	1.7769	0.4943	0.9829	0.9437	0.168710
DWT +HVS (proposed)	Books	Haar	**4.4663**	**0.8899**	**0.9997**	**0.9990**	**0.155442**
DWT (max. selection) [3]	Books	Haar	1.9312	0.5087	0.9898	0.9440	0.174342
DWT (Average) [4]	Books	Haar	1.7976	0.5021	0.9840	0.9483	0.174099
DWT+HVS (proposed)	Clock	Haar	**4.4910**	**0.9166**	**0.9997**	**0.9992**	0.220077
DWT (max. selection) [3]	Clock	Haar	1.9900	0.4468	0.9840	0.9429	0.180629
DWT (Average) [4]	Clock	Haar	2.1027	0.4450	0.9816	0.9542	**0.179576**
DWT+HVS (proposed)	Disk	Haar	**3.9216**	**0.8958**	**0.9995**	**0.9978**	**0.156922**
DWT (max. selection) [3]	Disk	Haar	1.8400	0.5239	0.9908	0.9468	0.177687
DWT (Average) [4]	Disk	Haar	1.8714	0.5147	0.9863	0.9437	0.176373
DWT+HVS (proposed)	Camera man	Haar	**3.8081**	**0.8580**	**0.9993**	**0.9945**	**0.153963**
DWT (max. selection) [3]	Camera man	Haar	1.9403	0.5563	0.9867	0.9436	0.178790
DWT (Average) [4]	Camera man	Haar	2.0102	0.5511	0.9886	0.9482	0.172847
DWT+HVS (proposed)	Toy	Haar	**3.4135**	**0.8691**	**0.9996**	**0.9960**	**0.164589**
DWT (max. selection) [3]	Toy	Haar	1.7508	0.4834	0.9937	0.9472	0.179240
DWT (Average) [4]	Toy	Haar	1.6738	0.4670	0.9904	0.9444	0.173390

4.2. Experimental Analysis

In general, problems are faced in considering the images to be fused. We created out-of-focus or multi-focus images by blurring some parts of the original image using low-pass filters. Blurring can be carried out by convolution with a Gaussian kernel. The basic wavelet family is Haar family, where various filters are considered to assess the performance. Experimental results for various images using Haar filter are presented in Table 1.

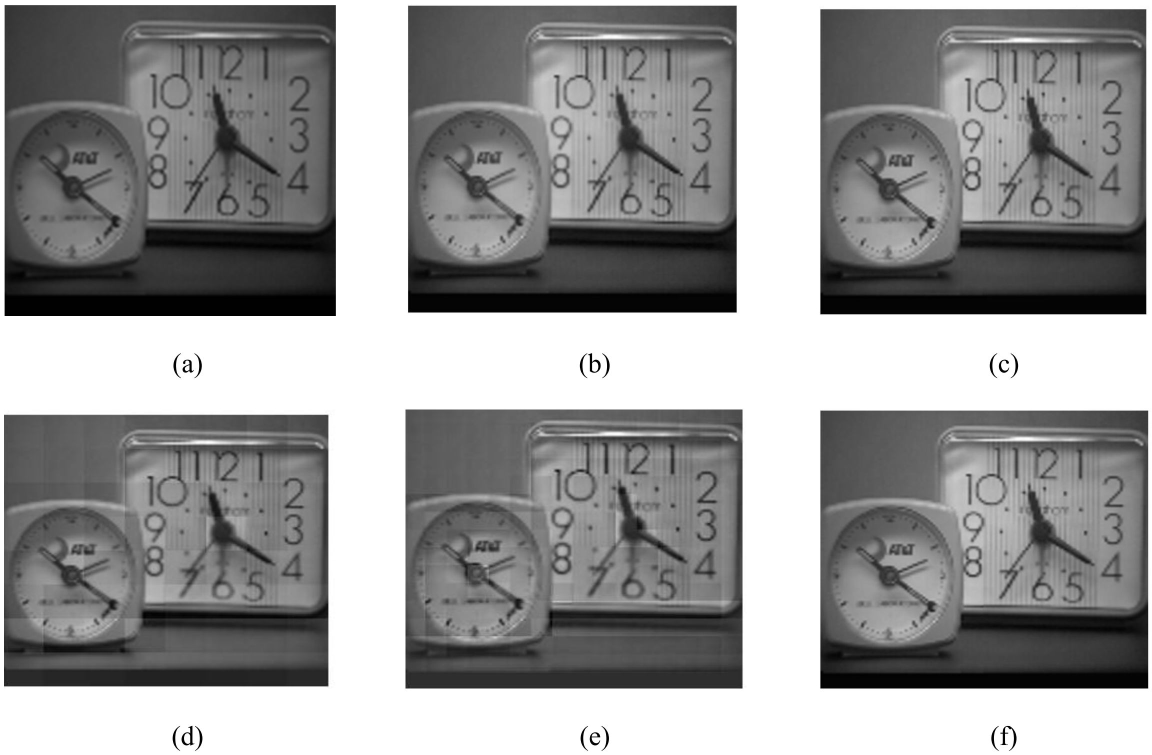

Figure 5 (a) benchmark image, (b) left blurred image, (c) right blurred image, (d) result of DWT (max. selection), (e) result of DWT (average), and (f) DWT+HVS (proposed method)

Figure 6. Cameraman image: (a) original image, (b) right blurred image, (c) left blurred image, and (d) is the fused image (DWT+HVS)

Table 2: Experimental results for the proposed method using different filters for the multi-focus (cameraman) image

Image	Filter	MI	ESOP	FSIM	NCC	Elapsed time in seconds
Multi-focus	Haar	3.8081	0.8580	0.9993	0.9945	**0.153963**
(cameraman)	Db2	3.8081	0.8580	0.9993	0.9945	0.191436
	Db5	3.7702	0.8440	0.9993	**0.9973**	0.236603
	Sym2	3.8081	0.8580	0.9993	0.9945	0.312608
	Sym6	3.8081	0.8580	0.9993	0.9945	0.240290
	coif1	3.7702	0.8440	0.9993	**0.9973**	0.205698
	Bior1.3	3.8081	0.8580	0.9993	0.9945	0.278921
	Bior3.5	3.8081	0.8580	0.9993	0.9945	0.247131
	rbio1.1	3.8081	0.8580	0.9993	0.9945	0.197905
	rbio2.2	3.7702	0.8440	0.9993	**0.9973**	0.207175

The results in Table 1 shows the MI, ESOP, FSIM, and NCC measurements were more in our proposed DWT+HVS technique than the other two methods. The most commonly used wavelets are Haar, Daubechies (db), Symlets (sym), and Coiflets (coif). Haar wavelet is the simplest and oldest wavelet. Most of the Daubechies wavelets are not symmetrical and Symlets are near symmetric wavelets. In Coiflets, the translation and scaling functions are much more symmetrical than the Symlets and Daubechies wavelets. The symmetry property of the wavelet is useful in reducing the phase errors in image processing. The experimental results are shown in Figure 5.

The regularity in wavelet families is useful in finding the best features for reconstruction of a signal or an image. In addition, all wavelet families obey the orthogonal properties. The results of DWT+HVS with different filters are executed on a multi focus (cameraman) image (given in Figure 6) and all the comparisons are made between the results of wavelet families calculated for the cameraman image. In Table 2, the run time (elapsed) time for a cameraman image is less in 'Haar' filters. The MI, ESOP, and FSIM measures are observed to be superior in 'rbio2.2' filters. The NCC result is good for 'coif1' among all other wavelet filters.In Table 2, the results for the proposed approach using different filters for the multi focus (cameraman) image are presented. The NCC values are better in db5, coif1, and rbio2.2. The run time is low for DWT+HVS using 'Haar' filter.

Experiments were also performed with naturally acquired images that are determined and tabulated in Table 3. The performance of MI, FSIM, and NCC measures were calculated in reference to the ground truth image. Edge strength orientation and preservation (ESOP), is a metric that does not require the ground truth image. The result in Figure7and Figure 8 shows that the proposed method is effective for all natural images. The medical image results are given in Figure 10.

Table 3**:** Experimental results performed with naturally acquired images

Fusion rule	Remote sensing images	Filter	ESOP	Elapsed time in seconds
DWT+HVS (proposed)	Field 1, Field 2	Haar	**0.5477**	**0.161753**
DWT (max. selection) [3]	Field 1, Field 2	Haar	0.0167	2.310168
DWT (Average) [4]	Field 1, Field 2	Haar	0.3580	0.178262
DWT+HVS (proposed)	gun 1, gun 2	Haar	**0.5927**	**0.166719**
DWT (max. selection) [3]	gun 1, gun 2	Haar	0.0312	1.921300
DWT (Average) [4]	gun 1, gun 2	Haar	0.3885	0.171202
DWT+HVS (proposed)	flir, lltv	Haar	**0.4429**	**0.160571**
DWT (max. selection) [3]	flir, lltv	Haar	0.0583	2.373511
DWT (Average) [4]	flir, lltv	Haar	0.4961	0.175707
DWT+HVS (proposed)	CT, MRI	Haar	**0.7266**	**0.163805**
DWT (max. selection) [3]	CT, MRI	Haar	0.2253	1.643815
DWT (Average) [4]	CT, MRI	Haar	0.6276	0.385489
DWT+HVS (proposed)	Remote 1,remote 2	Haar	**0.5787**	**0.163989**
DWT (max. selection) [3]	Remote 1,remote 2	Haar	0.0312	1.724461
DWT(Average) [4]	Remote 1,remote 2	Haar	0.4118	0.171512

Figure7. Battle field images: (a) field 1 image, (b) field 2 image, and (c) fused image (DWT+HVS)

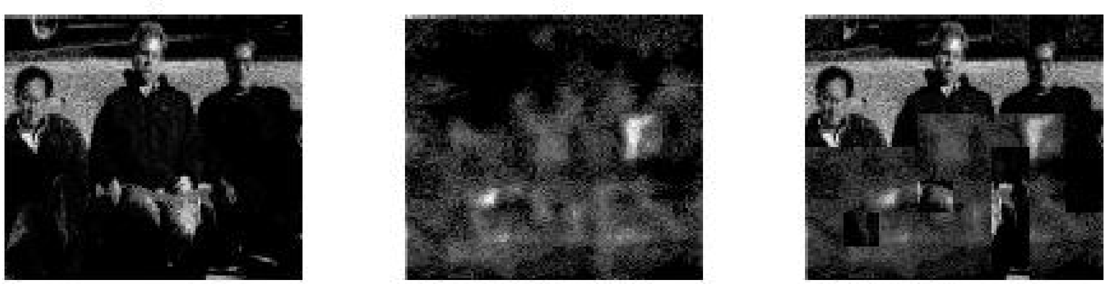

Figure8. Remote sensing images: (a) gun 1 image, (b) gun 2 image, and (c) the fused image (DWT+HVS)

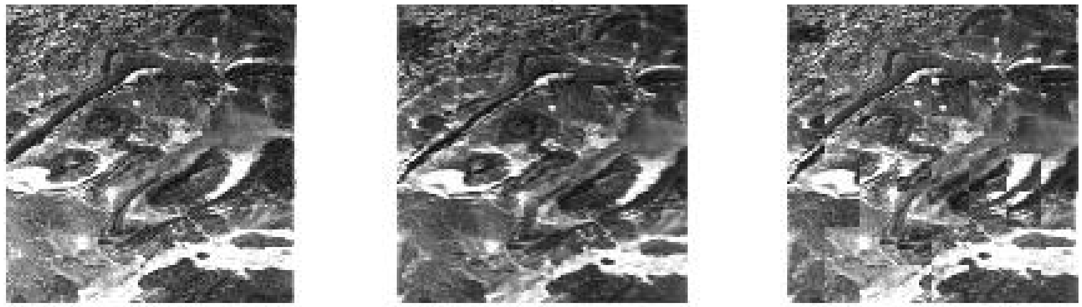

Figure9. Remote sensing images: (a) remote1 image, (b) remote2 image, and (c) the fused image (DWT+HVS)

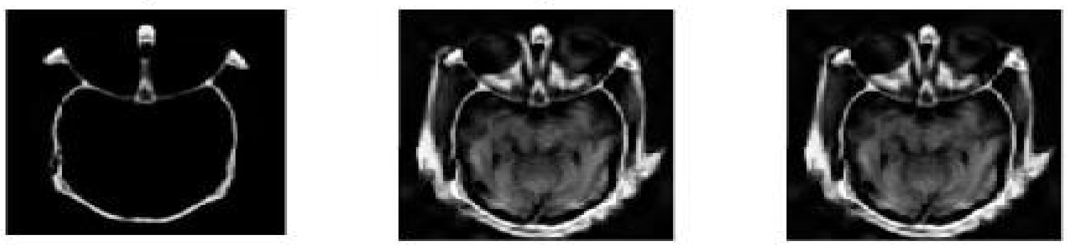

Figure 10. Medical images: (a) CT image, (b) MRI image, and (c) the fused image (DWT+HVS)

The experimental results for the remote sensing images (Figure 9) using different filters are given in Table 4, which show that the calculated ESOP of the proposed method using 'Haar' filter is found to be superior to all other measurements. However, the run time is low for DWT average using 'Haar' filter [4].

Table 4: Experimental results for the remote sensing images using different filters

Fusion rule	Filter	ESOP	Elapsed time
DWT+HVS (proposed)	Haar	**0.6678**	0.413864
DWT (max.selection) [3]	Haar	0.0348	1.921300
DWT (Average) [4]	Haar	0.3885	**0.177191**
DWT+HVS (proposed)	Db2	0.5927	0.189545
DWT (max.selection) [3]	Db2	0.0396	2.256725
DWT (Average) [4]	Db2	0.2513	0.193051
DWT+HVS (proposed)	Db5	0.5927	0.232771
DWT (max.selection) [3]	Db5	0.0364	2.372006
DWT (Average) [4]	Db5	0.3832	0.206951
DWT+HVS (proposed)	Sym2	0.5927	0.184902

DWT (max.selection) [3]	Sym2	0.0396	2.233882
DWT (Average) [4]	Sym2	0.2513	0.187266
DWT+HVS (proposed)	Sym6	0.5927	0.241161
DWT (max.selection) [3]	Sym6	0.0390	2.392888
DWT (Average) [4]	Sym6	0.2555	0.217881
DWT+HVS (proposed)	coif1	0.5927	0.196165
DWT (max.selection) [3]	coif1	0.0365	1.990912
DWT (Average) [4]	coif1	0.3743	0.192766
DWT+HVS (proposed)	Bior1.3	0.5927	0.219888
DWT (max.selection) [3]	Bior1.3	0.0394	2.155807
DWT (Average) [4]	Bior1.3	0.3632	0.207811
DWT+HVS (proposed)	Bior3.5	0.5927	0.259649
DWT (max.selection) [3]	Bior3.5	0.0364	2.137232
DWT (Average) [4]	Bior3.5	0.2610	0.243520
DWT+HVS (proposed)	rbio1.1	0.5927	0.192448
DWT (max.selection) [3]	rbio1.1	0.0348	2.100788
DWT (Average) [4]	rbio1.1	0.3885	0.191210
DWT+HVS (proposed)	rbio2.2	0.5927	0.209056
DWT (max.selection) [3]	rbio2.2	0.0375	2.012377
DWT (Average) [4]	rbio2.2	0.3377	0.216133

Table 5: Experimental results measuring the score for blocking artifacts

Fusion rule	Multi-focus image	Filter	Score
DWT+HVS (proposed)	Clock	Haar	**21.5581**
DCT+ Variance+ CV [22]	Clock	---	21.4902

The image fusion score is a measure for blocking artifacts. If the score is less, then the blocking artifacts are high, and vice versa. These comparisons are given in Table5.

Conclusion

In this paper, the DWT+HVS method is applied for image fusion and the perceptual important information is selected from the source images by using HVS. The weights measured from the results of the proposed approach of DWT+HVS surpasses the previous results. In addition, the proposed method is proved to be more efficient than other approaches, when the source images are in JPEG2000 format or the fused image is

stored or transmitted in JPEG2000 format. It is, thus, more appropriate for real-time applications. The blocking artifacts are less in the proposed method when compared to the DCT based methods. This method even suits to the medical imaging and remote sensing images. In the future scope, a similar fusion process can be applied on all other multi resolution transforms.

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